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Growth Profiles in English Class Self-Efficacy and Their Learning Effectiveness in the EFL Context

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This longitudinal study used data from the Busan Educational Longitudinal Study (BELS) to identify growth profiles of English class self-efficacy (ECS) over three years and their associations with English class comprehension, engagement, and achievement. A middle school student sample from 2016 to 2018 BELS comprised 3,038 students (1,394 females and 1,644 males) from 56 middle schools in South Korea. Using a person-centered approach with M*plus* 8.4, a higher-order growth mixture modeling (GMM) yielded three distinct growth trajectories of ECS: 82.8% of initially high and slowly decreasing (HSD) group, 9.7% of intermediate high and decreasing (IHD) group, and 7.5% of low but increasing (LI) group growth profiles. Results indicated that English class comprehension, engagement, and achievement showed statistically significant mean differences across each growth profile of ECS. The identified ECS growth profiles can be used to tailor intervention measures. Empirical findings are discussed in terms of pedagogical implications in applied language learning and teaching practices and further research.

Key words: English class self-efficacy, English class comprehension, English class engagement, English achievement, Higher-order growth mixture model

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1. INTRODUCTION

Motivation can significantly impact an individual's behavior (Nevid, 2013). With the transition of motivational research towards a cognitive-situated and process-oriented paradigm, investigations have centered on the dynamic cognitive states of individual learners about their self-perceptions (Dörnyei, 2014; Ushioda, 1998). A consensus among academics indicates that an individual's impression of their skills significantly influences motivation, and the cognitively defined construct of self-efficacy belief has garnered heightened research interest (Busse & Walter, 2013; Lim & Lee, 2016; Phan, 2012).

Self-efficacy is a cognitive framework regarding an individual's conviction in their capacity to execute specific learning activities or actions. It is regarded as one of the fundamental motivational constructs. Students possessing a robust sense of self-efficacy are more inclined to undertake challenging tasks, invest considerable effort, persist despite learning obstacles, accurately assess their academic performance, exhibit heightened interest in subjects, and demonstrate superior self-regulation compared to their peers with a diminished sense of self-efficacy (Bandura, 1997).

Hence, students who possess confidence in their capabilities generally achieve greater academic performance (Bandura, 1997; Pajares & Urdan, 2006; Schunk & Hanson, 1989). Previous research indicates that self-efficacy belief is a significant predictor of learning engagement (Galla et al., 2014) and achievement (Multon, Brown, & Lent, 1991; Schnell, Ringeisen, Raufelder, & Rohrmann, 2015; Talsma, Schüz, Schwarzer, & Norris, 2018).

Dörnyei (2007) indicates that research on second language motivation has focused on classroom-specific elements, yielding valuable educational implications pertinent to classroom practice. Students in a language class should engage in learning activities. As a prerequisite of classroom engagement, the construct of self-efficacy deserves to be investigated in foreign or second language (L2) classroom learning contexts.

Methodologically, given that motivation is a dynamic state, the conventional cross-sectional research approach is limited to capturing fine-grained changes that occur during the learning process. Namely, increasing research emphasis is put on using a longitudinal research framework that can investigate growth in motivational processes (Schunk & Greene, 2018). Thus, a longitudinal research design is essential for examining the development of self-efficacy across time.

Some previous research has explored the longitudinal change in self-efficacy using a variable-centered approach (Hornstra, van der Veen, Peetsma, & Volman, 2013; Phan, 2012). In L2 English learning, a longitudinal study reported that self-efficacy beliefs are key predictors of learning outcomes (Hornstra, van der Veen, & Peetsma, 2016). Additionally, the longitudinal changes in students' L2 English self-efficacy explained their students' class comprehension, class engagement, and achievement in the English learning context (Oh, 2022).

However, conventional longitudinal methods, such as latent growth curve modeling (LGCM) or curve-of-factors modeling (CFM), postulate that only one development trajectory can represent a population, assuming that variables influence the growth factors uniformly across all individuals. From a methodological perspective, estimating parameters with a singular growth model oversimplifies the diverse growth patterns within subgroups.

Recently, a growth mixture modeling (GMM) approach emerged as a more rigorous alternative method for in-depth information about unobserved heterogeneity within a population. Unlike variable-centered approaches, the focus of the person-centered approach is on the relationships between individuals, and the goal of a GMM is to classify individual students into distinct subgroups (Nylund, Asparouhov, & Muthén, 2007).

Despite the promising possibilities, the GMM approach remains embryonic in SLA research. This study aims to illustrate the application of GMM utilizing a comprehensive panel data set gathered over three years from Korean middle schools. This study specifically aimed to illustrate (a) the identification of latent growth classes and the determination of the optimal number of such classes, (b) the analysis of initial status and growth trajectories for English class self-efficacy (ECS) within distinct classes, along with the interpretation of these classes based on their growth pattern characteristics, and (c) the variation in classroom effectiveness corresponding to each growth trajectory.

In sum, this study identifies distinct ECS growth trajectories and evaluates their impact on engagement and achievement. Accurate classification is required to design appropriate intervention measures and processes that identify students in need so that remedial efforts or intervention can be targeted to those who require them the most.

2. LITERATURE REVIEW

A consensus among researchers indicates a decline in student motivation over time (Archambault, Eccles, & Vida, 2010; Jacobs, Lanza, Osgood, Eccles, & Wigfield, 2002). Although extensive research indicates average decreases in motivation, not all students display identical patterns of motivational change (Gottfried, Marcoulides, Gottfried, & Oliver, 2009; Wang, Chow, Degol, & Eccles, 2017). Some students' motivation may diminish sharply over time, while others' motivation may remain consistent or even escalate throughout their academic pursuits. Consequently, concentrating solely on the average trajectory of student motivation through the traditional latent curve growth modeling (LCGM) method may neglect the possible heterogeneity of these developmental patterns.

Numerous studies have shown that believing in one's own abilities has a positive effect on one's performance in school and other areas of life (Bandura, 1997; Pajares, 1997; Raoofi, Tan, & Chan, 2012; Schunk & Pajares, 2002; Woodrow, 2006). In terms of self-dynamics, it is essential to understand developmental processes that may encompass stability, gradual or sudden change, and cumulative variations (Mercer, 2011). Many educators also believe self-efficacy is a major predictor of academic achievement and performance (Hsieh & Kang, 2010; Lane & Lane, 2001; Pajares & Urdan, 2006). However, according to Shapka and Keating (2005), in order to detect changes in self-beliefs over time, panel data, ideally longer than one year, must be used.

Caprara et al. (2008) established a representative empirical longitudinal research design and methodology for measuring self-efficacy growth in students aged 12 to 22. The study, utilizing LGCM, revealed a decline in students' self-efficacy beliefs over time. Additional research (Oh, 2022; Pajares & Graham, 1999) has corroborated the advantages of longitudinal studies, indicating that self-efficacy is not a fixed trait but a changing state that fluctuates over time.

Phan (2012) gathered data from 339 Australian elementary school students in the third and fourth grades at four intervals over one year to examine the growth trajectory of their math and English self-efficacy, revealing an increase in both English self-efficacy and academic achievement. Additionally, Phan (2013) investigated the growth trend in academic self-efficacy among middle school students every six months for two years, demonstrating an increase in self-efficacy from the first to the third measurement point (wave), with intervals of seven months, followed by a decline at the fourth measurement. Furthermore, individual differences in the pattern of change were discovered. A study in the United Kingdom examining changes in university students' motivation to learn German revealed a decline in self-efficacy beliefs (Busse & Walter, 2013).

Kim (2012) and Yoon and Lim (2013) utilized panel data in their research on self-efficacy within the EFL Korean context, revealing that middle school students' English self-efficacy progressively diminished from the first to the third grade. The initial level and the growth rate in variance were both significant, implying that the students' English self-efficacy exhibited distinct trajectories. Lim and Lee (2016) contended in a longitudinal study employing multivariate latent growth modeling that the English self-efficacy of middle school students increased over time and positively predicted their English achievement.

In fact, growth trajectories found in previous L2 research have been mixed such that English self-efficacy has been shown to increase (Oh, 2022) and decline (Otis, Grouzet, & Pelletier, 2005) during secondary education. The inconsistencies in prior research prompt an inquiry into the potential variability in students' developmental trajectories of English self-efficacy during adolescence.

Remarkably, in a study of the latent profile analysis (LPA) of English as a Second Language (ESL) learners' self-efficacy in South Korea, three distinct groups were identified: low, medium, and high self-efficacy profiles (Kim, Wang, Ahn, & Bong, 2015). Therefore, a better understanding of distinct growth patterns and their effectiveness could help SLA researchers to develop customized measures and policies of support based on their membership of ECS growth patterns among secondary school students. Previous research, as mentioned above, has suggested that students' ECS can be categorized into distinct growth trajectories. This study aims to empirically establish the basis for identifying subgroup heterogeneity among Korean students ECS, thereby providing evidence for implementing tailored, differential interventions for each group.

2.1. ECS and English Class Engagement

Recent focus in the L2 motivation literature on student engagement has shed light on how to transform of learners' L2 motivation into observable language learning behavior (Hiver, Al-Hoorie, & Mercer 2021; Mercer & Dörnyei, 2020). Although behavioral engagement refers to students' attendance or overt behavioral efforts, authentic quality engagement is more concerned with time spent on classroom learning tasks, the amount of information students learn in class, and students' class-taking attitude (Al-Hoorie, 2018).

The importance of self-efficacy beliefs in motivating learning engagement has been well-researched in the school context (Schunk, Pintrich, & Meece, 2008). Engagement is a multifaceted construct encompassing cognitive, affective, and behavioral dimensions (Li & Lerner, 2013). Therefore, a comprehensive structure of English class engagement can be delineated based on students' cognitive, affective, and behavioral dimensions.

The cognitive dimension is conceptualized based on how well students understand what they learn in class (Oh, 2022; Oh & Cha, 2017). As a result, students who comprehend the learning content well participate in this dimension. The subsequent dimension is the affective dimension, which pertains to students' emotions, attitudes, interests, and perceptions regarding school-related activities (Finn, 1989). Finally, the behavioral dimension refers to students' behavioral disposition and behavior when approaching and engaging in school-related activities (McDermott, Mordell, & Stoltzfus, 2001). Participation and involvement in classroom activities and discussions are examples of such behaviors (Fredricks, Blumenfeld, & Paris, 2004). To summarize, engaged students may demonstrate an enthusiastic attitude toward learning, participate attentively in classroom activities, and comprehend what was taught in the lesson.

Classroom engagement is a necessary prerequisite for high-quality learning and academic achievement in school. Moreover, additional research indicates that self-efficacy may fluctuate as students participate in foreign language acquisition and attain proficiency over time (Mercer, 2012). L2 class engagement is defined as being committed to one's learning and completely immersed in class learning tasks (Schaufeli, Martnez, Pinto, Salanova, & Bakker, 2002). Self-efficacy is associated with engagement as it encourages individuals to exert additional effort to accomplish a task, leading to increased task involvement (Diseth, 2011; Ouweneel, Le Blanc, & Schaufeli, 2011). A longitudinal study investigating the relationship between self-efficacy and its impact on L2 class comprehension and participation demonstrated a positive correlation (Oh, 2022; Ryu & Seo, 2015). This study explored the impact of English self-efficacy growth profiles on students' classroom engagement, specifically in terms of English class comprehension, attitude, and participation.

2.2. ECS and English Achievement

Self-efficacy has been consistently associated with elevated academic achievement (Lane & Lane, 2001; Oh 2022; Phan, 2012; Pintrich & De Groot, 1990; Schunk & Pajares, 2002). Multon et al. (1991) documented a positive correlation between efficacy beliefs and academic achievement in a meta-analysis of self-efficacy research spanning over a decade. Similar positive associations were also identified among Norwegian undergraduate students (Diseth, 2011).

Numerous SLA research findings demonstrate that self-efficacy is a crucial determinant of learning outcomes and success (Chemers, Hu, & Garcia, 2001; Doordinejad & Afshar, 2014; Li & Wang, 2010; Lim & Lee, 2016; Mills, Pajares, & Herron, 2007; Oh, 2022; Rahemi, 2007; Rahimi & Abedini, 2009). Mills et al. (2007) identified a significant connection between reading self-efficacy and proficiency in reading, as well as between listening self-efficacy and listening proficiency. Tılfarlıoğlu and Cinkara (2009) analyzed the relationship between self-efficacy and English proficiency in third-grade high school students in Northern Tehran. A statistically significant association was established between self-efficacy and English performance.

As researchers in L2 motivation explored theoretical frameworks in educational psychology to deepen their comprehension of language acquisition, self-efficacy gained more prominence. Mills et al. (2007) investigated the influence of self-efficacy beliefs and various motivational factors on the academic achievements of 303 intermediate French college students. The results indicate that French grade self-efficacy predicted French success, as measured by final course grades. In 2007, Rahemi conducted a study examining English self-efficacy and EFL achievements among senior high school students with low proficiency levels. The study's results demonstrated that English self-efficacy significantly influenced EFL achievement. In Hsieh and Kang's (2010) study of 192 ninth-grade English language learners in Korea, self-efficacy emerged as a strong predictor of foreign language achievement. Multiple regression models showed that individuals with a greater sense of effectiveness in executing English-related tasks achieved better scores on tests.

Rahimi and Abedini (2009) performed another study investigating the relationship between EFL learners' self-efficacy beliefs about listening comprehension and undergraduate English learners' listening proficiency. The study's findings indicate a significant association between listening comprehension self-efficacy and listening proficiency. Self-efficacy facilitates effective learning.

Research involving Chinese, German, and Korean university students demonstrated statistically significant positive correlations between examination scores and English self-efficacy, as measured by the Survey Questionnaire of English Self-Efficacy (Kim et al., 2015; Wang, Schwab, Fenn, & Chang, 2013). Liem, Lau, and Nie (2008) identified an indirect influence of self-efficacy beliefs on English language test scores among a nationally representative sample of Singaporean secondary students enrolled in English courses.

The influence of L2 English self-efficacy on achievement was validated in the context of Korean EFL (Kim, 2012). Hsieh and Kang (2010) identified a positive effect of L2 self-efficacy on L2 achievement in their research including 192 Grade 9 L2 learners in Korea. Utilizing the KELS panel data set, Park and Jun (2007) investigated the relationship between L2 self-efficacy and achievement, revealing that L2 self-efficacy exerted the most significant influence on L2 achievement. Oh and Cha's (2017) multi-level SEM study found that English class engagement mediated the positive effect of English self-efficacy on English achievement. That is, it is possible to infer a positive relationship between self-efficacy and English class engagement. English class engagement is operationally defined in the study as the degree to which students participate in an English class and refers to the amount of time they commit to learning tasks and activities during class (Kuh, 2009).

Some researchers also discovered an indirect effect of self-efficacy beliefs on English language test scores. Consequently, enhancing the self-efficacy beliefs of English language learners is essential to their language development and should be integrated into pedagogical strategies (Wang et al., 2013).

3. METHODOLOGY

3.1. Sample

The Busan Educational Longitudinal Study (BELS), a large-scale longitudinal panel research project administered annually by the Busan Office of Education in South Korea, was used in this study to identify distinct growth patterns of middle school students' L2 ECS and differences in learning outcomes based on the growth profiles. The BELS is a multi-wave, longitudinal study encompassing surveys of parents, educators, and school administrators. Schools were selected in accordance with their regional distribution and student population through a stratified sampling method, and two classes from each sampled school were randomly resampled. This study included 3,038 students (male: 1,644, 54.1%, female: 1,394, 45.9%) in Grades 7-9 from 56 South Korean middle schools.

The survey was conducted with the collaboration of a partner teacher, who obtained consent forms from the participants' legal guardians for their participation in the survey. The survey procedure was supervised by qualified research assistants. A briefing session was held to assist partner teachers in conducting the survey, and then the main survey and achievement test were conducted from July 3 to July 17, 2018, according to each school's schedule. The BELS survey was administered three times during three middle school years: Year 1 (July 2016), Year 2 (July 2017), and Year 3 (July 2018).

3.2. Measure

The BELS collected data annually and screened it for analysis using a stratified random sampling technique. We used students' responses to survey items in the BELS Codebook labeled as L2 English class self-efficacy, which had been pre-validated based on theoretical background.

The Motivated Strategies Learning Questionnaire for Adolescents (Pintrich & DeGroot, 1990) scale was adapted to measure the L2 ECS construct. Four indicator items were rated on a 5-point Likert-type scale ranging from 1 (strongly disagree) to 5 (strongly agree), measuring efficacious appraisals of ability expectations in L2 English classroom contexts (Kim, Kim, Kang, Kim, & Shin, 2007). Specifically, the L2 ECS survey items included (a) I'm confident to understand the most difficult contents in English textbooks; (b) I'm confident I can do an excellent job on my English assignments; (c) I'm confident I can receive an excellent grade in an English exam; (d) I have confidence that I can master and proficiently use what I have learned in English class. High internal consistency reliability estimates for each time point as indicated by Cronbach's alpha (α = .939, .945, and .948 for L2 ECS in order) with Korean middle school students (N = 3,038) were reported.

3.2.1. L2 English class engagement

The measures of outcome variables in Grade 9 were based on students' responses about their comprehension, participation, and attitudes in their English classes (Oh, 2020; 2022). The L2 class engagement consists of three components: (a) the degree of L2 class comprehension (1 = 20% or less, 2 = 21-40%, 3 = 41-60%, 4 = 61-80%, 5 = 81% or more), (b) the duration of participation or attention to the L2 class (1 = 0-10 min, 2 = 11-20 min, 3 = 21-30 min, 4 = 31-40 min, 5 = 41 min or more (with 1 class hour = 50 mins)), and the L2 class taking attitude is composed of 5 items with 5-point Likert scale: 1. I concentrate on English class, 2. I am actively involved in English class, 3. I do my English homework, 4. I prepare in advance what I will learn in English class, 5. I review what I learned in English class. The Cronbach's alpha value for the L2 class taking attitude items is .877.

3.2.2. L2 English academic achievement

English academic achievement was assessed in terms of the student's scores on standardized academic English achievement tests in Year 3. Students' national achievement test scores, collected through institutional records, were used as outcome variables. We used the average of standardized scores in English subjects, commonly required for college applications in South Korea, and have been used as an important measure of academic outcome (Lee & Seo, 2019).

Specifically, the standardized English achievement test, developed by BELS, consisted of a listening (10 items, 31 points) and a reading section (18 items, 69 points) for a total of 28 multiple-choice questions. Even though acknowledging that there are many other aspects to language proficiency, we used a measure of L2 achievement test consisting of reading and listening components.

3.3. Data Analysis

All analyses were conducted utilizing the M*plus* software, version 8.4 (Muthén & Muthén, 2019) with the robust maximum likelihood estimator. Figure 1 illustrates that the first-order measurement model at each time point, t, is defined by: the measurement intercepts (τ_{jt}) for each manifest indicator (y_{jti}), the factor loading for each indicator variable (λ_{jt}), a latent factor variable (η_{ti}), and the indicator-specific variance (ε_{jti}), where the subscript j represents a specific indicator of the first-order factor model and the subscript i refers to individual respondents. Consequently, the equation for the observed indicator y_{jti} can be expressed as:

$$\mathrm{ECS}_{jti}\ \mathrm{y}_{jti} = \tau_{jti} + \lambda_{jt}\ \eta_{ti} + \varepsilon_{jti}, \quad \varepsilon_{jti} \sim \mathrm{NID}\ (0, \sigma^2_{jt}) \tag{1.1}$$

In the second-order structural model, the first-order latent factors (η) serve as indicators for the second-order factors. For each intercept and slope factor, a mean (μ) and variance (ψ) are estimated. Consequently, the model equations are expressed as follows:

$$\mathrm{ECS}_{ti}\ \eta_{ti} = \pi_{0i} + \lambda \times \pi_{1i} + \zeta_{it}, \zeta_{it} \sim \mathrm{NID}(0, \psi_t) \tag{1.2}$$

$$\pi_{0i} = \mu_{00} + \zeta_{0i}, \zeta_{0i} \sim \mathrm{NID}(0, \psi_{00}) \tag{1.3}$$

$$\pi_{1i} = \mu_{10} + \zeta_{1i}, \zeta_{1i} \sim \mathrm{NID}(0, \psi_{11}) \tag{1.4}$$

$$\Psi = \begin{bmatrix} \psi 00 & \\ \psi 10 & \psi 11 \end{bmatrix} \quad (1.5)$$

μ_{00} represents the average baseline values of the second-order trajectories when linear time increments of 0, 1, and 2 are utilized, while μ_{10} indicates the mean slope. The residuals are presumed to be normally and independently distributed (NID) with a mean of zero and a variance-covariance structure (ψ).

A GMM methodology posits that a categorical latent variable, C, determines the most possible category (i.e., class or sub-group) to which each individual belongs. As a result, individuals are assigned to one of the specific second-order growth profiles that most accurately corresponds to their distinct growth trajectory. The equation for the second-level growth curve for individual i is categorized by the latent growth class (q = 1, 2, 3, …, Q):

$$\pi_{q0i} = \mu_{q00} + \zeta_{q0i},\ \zeta_{q0i} \sim \mathrm{NID}(0,\ \psi_{q00}) \quad (1.6)$$

$$\pi_{q1i} = \mu_{q10} + \zeta_{q1i},\ \zeta_{q1i} \sim \mathrm{NID}(0,\ \psi_{q11}) \quad (1.7)$$

$$\Psi q = \begin{bmatrix} \psi q00 & \\ \psi q10 & \psi q11 \end{bmatrix} \quad (1.8)$$

μ_{q00} and μ_{q10} denote the mean intercept and slope in latent trajectory class q, respectively. The errors ζ_{q0i} and ζ_{q1i} signify the variability of the estimated intercepts and slopes among individuals within each growth trajectory class. The variance-covariance structure of these error terms is represented by ψ_q, with ψ_{q00} and ψ_{q11} indicating the error variances of the estimated intercept and slope factors, respectively, while ψ_{q10} denotes the covariance between the intercept and slope factors within the latent trajectory class q. The subscript q indicates that the majority of parameters may vary among the estimated latent trajectory classes. Thus, each second-order latent class may be defined by its distinct growth model, determined by class-specific parameters, including the variance and covariance structure (ψ_q) and the means (i.e., μ_{q00} and μ_{q10}) of growth.

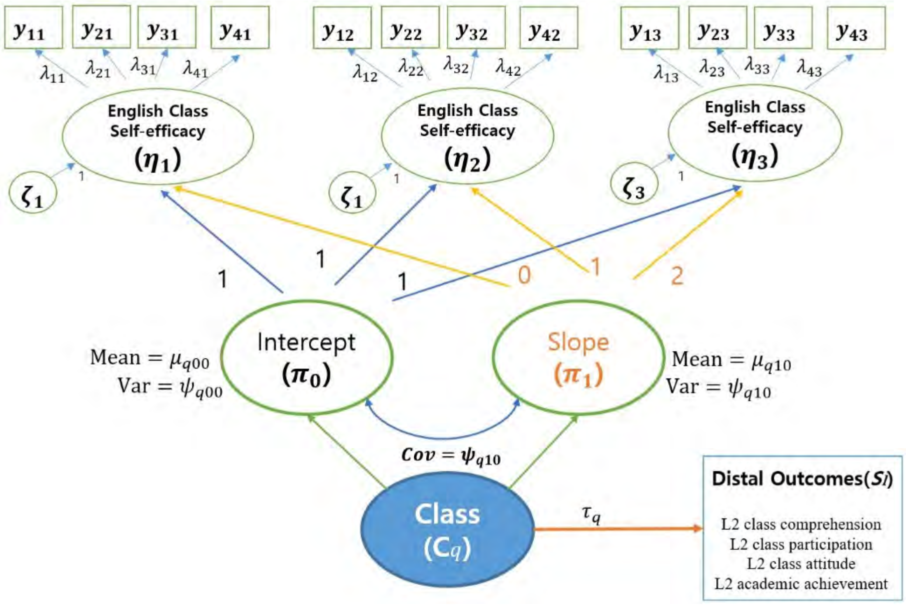
Following that, the incorporation of continuous distal outcomes in a GMM is illustrated. When including continuous outcomes, class means are estimated, and the statistical significance of variations in these means is examined using a mean equality test.

Figure 1 illustrates the conditional higher-order GMM specification incorporating predictors and distal outcomes. In the estimation of a conditional GMM utilizing a new model-based approach for analyzing auxiliary distal outcomes, the distal outcomes do not influence the GMM classification (Lanza, Tan, & Bray, 2013). This technique allows researchers to account for the variance of a distal outcome variable when forecasting a distal outcome.

As is common in longitudinal studies, certain subjects are absent during one or more data collection intervals. To address missing values, full information maximum likelihood with robust standard errors, as provided in M*plus* 8.4 (Muthén & Muthén, 2019), was employed for parameter estimation, as it includes all available data in the analysis, enabling generalizations of results to the population (Benner & Graham, 2009).

FIGURE 1

The Diagram of a Conditional Second-Order GMM of L2 Self-efficacy



Note. Cov = covariance; Var = variance; Subscript q is a categorical class variable q (q = 1, 2, 3, ⋯, Q); Each observed indicator (y_{jti}); the factor loading for each indicator variable (λ_{jt}); a latent factor variable (η_{ti}); the indicator-specific variance (ε_{jti}); τ_q = An intercept (threshold) of distal outcomes for q class

4. RESULTS

4.1. Descriptives

Table 1 shows the descriptive statistics with internal consistency (Cronbach's Alpha) for the constructs of students' ECS indicators across the three measurement time points (Waves). A brief examination of the descriptive statistics revealed that the mean ECS had a decreasing trend over the years. Within each time point, indicator items strongly correlate with one another, assuming that their correlation is attributable to an underlying construct. Furthermore, each scale's items correlate across time points. The data distribution for the ECS scales was examined and found to be normal (skewness range = -.503 to -.995; kurtosis range = -.051 to -.491) based on the guidelines of skewness (below 3) and kurtosis index (below 10) (Kline, 2010).

TABLE 1

Descriptive Statistics of Indicators for ECS Across Three Waves (Grades 7 to 9)

ECS Indicators		*N*	*M*	*SD*	Skew	Kurtosis	α
Wave 1 (The year 2016; Grade 7)	Item 1	3,007	3.90	1.104	-.709	-.237	.930
	Item 2	3,008	4.15	1.000	-.995	.405	
	Item 3	3,005	3.80	1.169	-.648	-.433	
	Item 4	3,001	3.91	1.106	-.720	-.204	
Wave 2 (The year 2017; Grade 8)	Item 1	2,838	3.76	1.100	-.546	-.355	.929
	Item 2	2,836	4.05	1.000	-.843	.217	
	Item 3	2,836	3.68	1.154	-.503	-.488	
	Item 4	2,833	3.79	1.092	-.568	-.319	
Wave 3 (The year 2018; Grade 9)	Item 1	2,825	3.73	1.131	-.558	-.389	.937
	Item 2	2,825	3.96	1.036	-.728	-.051	
	Item 3	2,827	3.66	1.163	-.523	-.491	
	Item 4	2,825	3.73	1.117	-.548	-.357	

Appendix displays all the indicator items' bivariate correlations for each scale of ECS and distal outcome variables. Pearson product-moment correlation coefficients demonstrate high and positive correlations among indicators of different time-point latent variables. All other correlation values were statistically significant.

Table 2 summarizes descriptive statistics about outcome variables, including the level of the L2 class comprehension, the duration of L2 class participation, L2 class-taking attitude, and the L2 achievement test scores. The level of L2 class comprehension item scale was 1 = 20% or less, 2 = 21 to 40%, 3 = 41 to 60%, 4 = 61 to 80%, 5 = 81% or more. The duration of the L2 class participation scale was 1 = 0-10 min, 2 = 11-20 min, 3 = 21-30 min, 4 = 31-40 min, and 5 = 41 min or more (with 1 class hour = 50 mins). The attitude of the L2 class consists of 5 items measured by a 5-point Likert scale: (a) I focus on my English class; (b) I actively engage in English class; (c) I regularly do my English homework; (d) I prepare in advance what I will learn in English class; (e) I review what I have learned in English class. For the L2 English achievement, the scaled score was used. The average scaled score on the L2 achievement test was 506.1 points.

TABLE 2
Descriptive Statistics for the Outcome Variables

Variables	*N*	*M*	*SD*	Description
The degree of L2 class comprehension	2,834	3.92	1.247	1 = 20% or less, 2 = 21-40%, 3 = 41-60%, 4 = 61-80%, 5 = 81% or more
The span of L2 class participation	2,834	3.63	1.202	1 = 0-10 min, 2 = 11-20 min, 3 = 21-30 min, 4 = 31-40 min, 5 = 41 min or more (with 1 class hour = 50 mins)
The degree of L2 class attitude	2,832	3.67	.974	5-point Likert scale Composite score of 5 items of L2 class-taking attitude
L2 academic achievement	2,817	488.95	51.439	Scaled scores of standardized English achievement test

4.2. Test for Longitudinal Measurement Invariance

In a higher-order GMM, longitudinal measurement invariance is an important assumption to ensure that the same construct is being represented across different measurement points over time (Meredith, 1993). Table 3 includes the model fit indices for each step of longitudinal factorial invariance in the ECS construct. First, the configural model (M2) fit indices demonstrated good model fit for the data (CFI =.994, RMSEA =.038), confirming the configural model assumption that these fit statistics indicate one underlying construct of ECS at each time point. Next, the assumption of weak invariance was tested by comparing M3 with M2. The results showed that the constraints in M3 do not significantly decrease the model fit compared to M2 (ΔCFI = 0, ΔRMSEA = .003). As a result, the assumption of weak invariance was also satisfied. Finally, when comparing M3 to M4, which adds constraints to keep the observed variable means equal across time, M4 did not significantly reduce model fit (CFI =.003, RMSEA =.007). Strong longitudinal invariance was proved to be tenable for the ECS scales, using measurement model tests with increasing invariance constraints.

TABLE 3
Model Fit Indices of Testing Measurement Invariance

Model	χ^2 (*df*)	Model comparison	$\Delta\chi^2$	CFI	ΔCFI	RMSEA	ΔRMSEA
Configural model (M2)	219.462*** (41)			0.994		0.037	
Weak invariance (M3)	224.762*** (47)	*p* = .506	5.3(6)	0.994	0	0.035	0.003
Strong invariance (M4)	345.232*** (55)	*p* = .000	120.47(8)	0.991	0.003	0.042	0.007

Note. M = Model; All of these models included autocorrelated errors.

4.3. The Latent Growth Trajectory of ECS

To do GMM, a conventional LGCM should be fitted to the data as a preliminary step. Fit statistics of the linear ECS model (CFI 0.994, TLI 0.992, RMSEA 0.037, SRMR 0.014) are excellent according to the guidelines (CFI, TLI $\geq$ 0.95, RMSEA $\leq$ 0.06, SRMR $\leq$ 0.05) (Hu & Bentler, 1999). Then, an unconditional LGCM was fitted to estimate the mean and the variance of intercepts and slopes across individual students. As shown in Table 4, findings indicate that the intercept in the initial measurement occasion was statistically significant (μ_{00} = 3.885, *SE* = .021, $p < .001$), which also varies across students (Ψ_{00} = .592, SE = .035, $p < .001$). Statistically, significant mean levels appeared for the intercept and variance, indicating an initial level of ECS greater than zero and varying across students, respectively. Besides, the overall growth rate (slope) in ECS across time was statistically significant (μ_{10}= -.087, *SE* = .010, $p < .001$) and significant variation across students (Ψ_{11} = .047, *SE* = .016, $p < .01$). Namely, although the average trajectory exhibited a decreasing trend, this pattern did not universally apply to all individuals.

TABLE 4

Parameter Estimates of Linear Unconditional Model for ECS

	M		Variance		*Covariance*
	Intercept	Slope	Intercept	Slope	
ECS	3.885^{***}	-0.087^{***}	0.592^{***}	0.047^{**}	-0.020

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

4.4. Determining the Optimal Number of Classes

The process of enumerating latent classes begins with considering a set of models with the same underlying LGCM structure and fitting an increasing number of latent classes to each model (Wang & Bodner, 2007). The best-fitting model will have the smallest information criteria indices. The values of information criterion indices for a sequentially increasing number of latent classes were plotted in Figure 2.

Figure 2 shows that using more than one class improves information criterion indices and that there is a sharp drop between the 3- and 4-class models before leveling off. However, when detecting the number of classes, it is important to distinguish a substantively meaningful number of classes with the help of other considerations rather than solely selecting the lowest point in the AIC, BIC, and SABIC curve (Kreuter & Muthén, 2008).

Hence, given that 3- and 4-class models were seemingly plausible, we compared the models using the Vuong-Lo-Mendell-Rubin (VLMR) likelihood ratio test (Lo, Mendell, & Rubin, 2003). This test was used for comparing the fit of a given model with a model containing one fewer class. For instance, the VLMR test comparing the 1-class model to the 2-class model yielded a significant result, indicating that the 1-class model should be rejected in favor of the 2-class model. To test the viability of the 3-class model, the second VLMR test comparing the 2-class model was conducted. In Table 5, the result showed a nonsignificant result, suggesting that the 2-class model should not be rejected in favor of the 3-class model. As a result, the VMLR and LMR LRT tests supported the 2-class model, but the BLRT test supported the 4-class model.

FIGURE 2

The Change of Information Criteria (AIC, BIC, SABIC) with the Number of Classes

Next, most of the model fit indices suggested that the 4-class model was the optimal model (e.g., lower AIC, BIC, and SABIC values, the highest entropy value, and statistically significant *p*-values for the BLRT). However, the results of the 4-class model were questionable because of the small class sizes (lower than 5%). The smallest group size (*n*) in the 4-class model was 2.4%. The existence of such a small class size is doubtful and meaningless for classification.

Similarly, the 2-class model shows statistically significant p-values for the VLMRT and LMR LRT and also BLRT. The entropy value is higher than the 3-class model, but there is also a group size of 3.9%. However, compared to the 2-class model, the 3-class model had a lower AIC, BIC, and SABIC, a lower but similar acceptable level of entropy value, and a statistically significant BLRT *p*-value.

Taking all the criteria information into consideration simultaneously, the 2- and 4-class models were rejected in favor of the 3-class GMM model. Namely, the 3-class model was selected as the optimal model because the model fit indices suggest that it fit better than the 2-class model and the 4-class model. In sum, determining the optimal number of classes should depend on a combination of factors in addition to fit indices and tests of model fit, including research question, parsimony, theoretical justification, and interpretability.

TABLE 5

Criteria for Latent Class Classification for the Growth Mixture Model

Criteria of classification (Fit statistics)		The number of model classes			
		2-class model	**3-class model**	4-class model	5-class model
Information Criteria	LL (No. of Parameters)	-36135.479(45)	**-35872.582(50)**	-35371.291(55)	-35316.719(60)[a]
	AIC	72360.957	**71845.164**	70852.581	-
	BIC	72631.766	**72146.063**	71183.569	-
	SABIC	72488.783	**71987.193**	71008.813	-
χ^2 test	VLMRT	-36324.698***	**-36135.479**	-35872.582	-
	LMR LRT	369.228***	**512.997**	978.183	-
	BLRT	-58384.036***	**-36135.479*****	-35872.582***	-
Entropy		0.944	**0.922**	0.993	-
Group ratio (%)	Class 1	96.1%	**7.5%**	9.9%	-
	Class 2	3.9%	**9.7%**	11.8%	-
	Class 3		**82.8%**	2.4%	-
	Class 4			75.9%	-
	Class 5				-

Note. Optimal model = Boldic style; LL = log-likelihood; No. of Parameters = Number of estimated (freed) parameters; AIC = Akaike's information criterion; BIC = Bayesian information criterion; SABIC = Sample size Adjusted BIC; VLMRT = Vuong-Lo-Mendell-Rubin likelihood ratio test; LMR-LRT = Lo-Mendell-Rubin Likelihood Ratio Test; BLRT = Bootstrap Likelihood Ratio Test; a = No repeated log-likelihood value (i.e., local maxima)

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

4.5. Identifying the ECS Growth Patterns

In Table 6, we identified three distinct ECS trajectories. Based on the mean level and growth rates observed across the three data waves, we labeled these growth trajectory patterns: low but increasing (Class 1), intermediate high and decreasing (Class 2), and high and slowly decreasing (Class 3).

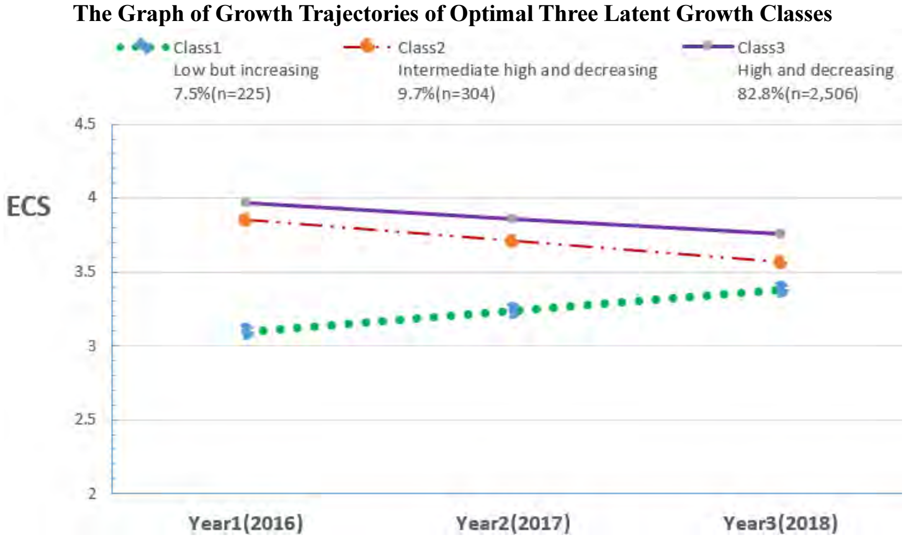
TABLE 6
Class-Specific Global Growth Parameters of the Second-Order Growth Mixture Models (SOGMMs)

SOCMM-CF (GMM-CI)	Initial level		Slope level		Factor covariance
	M	Variance	*M*	Variance	
Low but increasing	3.092***	0.597***	0.143**	0.053**	-0.021
Intermediate high and decreasing	3.854***		-0.144***		
High and slowly decreasing	3.966***		-0.104***		

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Figure 3 depicts the estimated mean growth curves for the three distinct ECS developmental profiles. The estimated class percentages are 7.5% (*n* = 225), 9.7% (*n* = 304), and 82.8% (*n* = 2,506), arranging the classes from low to high. Class 1 students have the lowest ECS and show a steady improvement over the three years of middle school. Even though recovering, at the last wave (Grade 9), Class 1 students' ECS had not reached the level of Class 2 students' level at their initial starting value. Students in Class 2 show an initial intermediate and slightly rapid decline in ECS. Class 3 students have the highest ECS scores and exhibit a similar growth pattern in ECS as Class 2 students, albeit with a slightly slower decline over three years. Namely, Class 3 students start out initially with the highest ECS and exhibit a slower decline during middle school. Class 3 was considered as a normative class because they accounted for a majority (82.8%) of the population.

FIGURE 3
The Graph of Growth Trajectories of Optimal Three Latent Growth Classes



4.6. Estimating a Conditional GMM of ECS with Distal Outcomes

Time-invariant covariates can be used to test if the emergent latent classes have the characteristics of the auxiliary variables predicted by theory. The study used the Lanza command's auxiliary option (DCON) and BCH to estimate the effects on distal outcomes (Lanza et al., 2013). τ_q indicates a threshold (intercept) of a distal outcome of class q as shown in Figure 1. When incorporating distal outcome variables, class means are estimated, and the statistical significance of the differences in these means is analyzed using a mean equality test. A Wald chi-square test was applied to test mean equality. The distal outcome results are shown in Table 7.

The findings revealed that the mean level of L2 learning outcome variables differed significantly across classes. Namely, the mean levels of the degree of L2 class comprehension were found to be significantly different between the 'High and slowly decreasing' vs. 'Low but increasing' class and 'Low but increasing' vs. 'Intermediate high and decreasing' class. However, for the degree of L2 class participation, all three classes have significantly different mean levels.

Besides, the mean level of L2 academic achievement varied significantly between the 'High and slowly decreasing' vs. 'Low but increasing' class and 'Low but increasing' vs. 'Intermediate high and decreasing' class. However, the mean levels and probabilities (or thresholds) of L2 academic achievement were not statistically different between the 'High and slowly decreasing' class vs. the 'Intermediate high and decreasing' class.

5. Discussion

This study was designed to investigate how L2 language teachers and policymakers can assist in providing insights and implications for the benefit of language learners as they strive to create positive beliefs about their abilities to learn the L2 language. In this present study, the authors applied a GMM modeling approach to identify distinct growth profiles of secondary school students' ECS development, which could spotlight potential differences in learning outcomes among the growth profiles within a large-scale panel dataset.

As a preliminary step, LGCM results revealed that the growth pattern of ECS decreased linearly, signifying that learner ECS will decrease as their grades go up. From an applied linguistics perspective, this observation was of particular interest, as it was found to be consistent with other previous research studies (Busse & Walter, 2013; Caprara et al., 2008; Kim, 2012; Otis et al., 2005; Yoon & Lim, 2013). These specific findings suggested a critical need to highlight how researchers should additionally trace negative linear trajectories of ECS beliefs. Similar to existing longitudinal studies that have been conducted (Caprara et al., 2008), these findings obtained from this present study accentuated the unstable paths and complex trajectories of ECS beliefs over their three-year course of schooling.

TABLE 7

The Mean and the Comparison of Outcome Variables Among Each Growth Class

Outcome variables	Class	*M*	*SE*	Mean Comparison between classes	X^2	*p*
The degree of L2 class comprehension	High and slowly decreasing	3.971 3.962	0.029 0.031	High and slowly decreasing vs. Low but increasing	19.773 14.668	.000 .000
	Low but increasing	3.415 3.449	0.122 0.128	High and slowly decreasing vs. Intermediate high and decreasing	3.816 1.096	.051 .295
	Intermediate high and decreasing	3.779 3.851	0.094 0.100	Low but increasing vs. Intermediate high and decreasing	5.592 6.167	.018 .013
The degree of L2 class participation	High and slowly decreasing	3.689 3.684	0.028 0.029	High and slowly decreasing vs. Low but increasing	31.086 18.496	.000 .000
	Low but increasing	3.053 3.140	0.111 0.121	High and slowly decreasing vs. Intermediate high and decreasing	8.214 6.183	.004 .013
	Intermediate high and decreasing	3.424 3.441	0.088 0.091	Low but increasing vs. Intermediate high and decreasing	6.882 3.978	.009 .046
The degree of L2 class attitude	High and slowly decreasing	3.720 3.714	0.023 0.024	High and slowly decreasing vs. Low but increasing	16.227 10.904	.000 .001
	Low but increasing	3.358 3.386	0.087 0.095	High and slowly decreasing vs. Intermediate high and decreasing	5.264 2.834	.022 .092
	Intermediate high and decreasing	3.549 3.581	0.071 0.074	Low but increasing vs. Intermediate high and decreasing	2.894 2.658	.089 .103
L2 academic achievement	High and slowly decreasing	3.720 3.714	0.023 0.024	High and slowly decreasing vs. Low but increasing	9.694 9.257	.002 .002
	Low but increasing	3.358 3.386	0.087 0.095	High and slowly decreasing vs. Intermediate high and decreasing	0.953 1.493	.329 .222
	Intermediate high and decreasing	3.549 3.581	0.071 0.074	Low but increasing vs. Intermediate high and decreasing	9.738 11.204	.002 .001

Note. In each cell, the upper values indicate DCON results, and the lower values indicate BCH results.

Considering the fact that ECS is amenable to change, teachers may be encouraged to develop a pedagogical intervention program to promote positive change and facilitate affirmative ECS beliefs over time. Likewise, positive change in ECS beliefs may include fostering instructional policies and practices in classroom settings. Having said this, group work or cooperative learning may encourage students' positive self-beliefs and elicit learning that engages in deeper absorption of knowledge and critical thinking.

In terms of research questions, we first uncovered three optimal numbers of distinct growth patterns (low, intermediate high, and high growth pattern groups) in students' ECS growth trajectories. The number of classes in the present study was classified using multiple information criteria and substantial meaning. We determined that the 3-class model was the best classification because it best represented the heterogeneity of ECS growth in middle school students. The classes represented the three different developmental profiles, or specifically, the three groups based on the level of ECS growth patterns. Further, growth mixture modeling revealed three growth trajectories of ECS: low but increasing (7.5%), intermediate high and decreasing (9.7%), and high and slowly decreasing (82.8%).

Secondly, these distinct three ECS student groups strongly supported previous LPA research findings that reported low, medium, and high self-efficacy profiles (Kim et al., 2015) and could also explain mixed research findings that reported increasing (Lim & Lee, 2016; Oh, 2022; Phan, 2012) or decreasing growth patterns (Busse & Walter, 2013; Caprara et al., 2008; Kim, 2012; Otis et al., 2005; Yoon & Lim, 2013) of L2 self-efficacy in a single model. From a practical standpoint, these findings suggest that educational policies should be aware of this visible pattern and reconsider intervention programs in order for them to be tailored to a specific group of students, particularly those from a low but increasing class. Instead of general policies, customized measures should be applied to discern each group of ECS pupils.

Next, the comparison analysis among each growth class showed statistically significant mean differences in the outcome variables, such as the degrees of L2 class comprehension, L2 class participation, L2 class attitude, and the degree of L2 academic achievement. Considering the mean differences among each group, these present findings were consistent with existing theoretical contentions (Bandura, 1997; Pajares, 1997) and indicated that L2 class effectiveness relates closely to ECS. This reliable predictive utility of ECS suggests that it may be necessary for students to remain or gain confidence in the English subject areas in order to engage in learning and ultimately be high achievers. Namely, these present findings fit well within the social cognitive theory.

Since ECS can be indicative of active student learning and persistent engagement in English classroom activities, it can be a useful predictor of self-regulated learning. The results of this study demonstrated that students with higher ECS are more willing to put in practice to improve their L2 class engagement (Galla et al., 2014; Hornstra et al., 2016; Oh, 2022) and achievement (Multon, Brown, & Lent, 1991; Schnell et al., 2015; Talsma et al., 2018), and thus have the tools to regulate the learning process more effectively than their weaker counterparts. Namely, students with higher levels of ECS appeared to exert more effort in class, which demonstrated stronger resolve and persistence.

In South Korea's intensely competitive educational environment, students face increasingly challenging academic assignments and consistently elevated parental expectations. Certain students experience failure and defeat during the initial phases of their education. This likely leads some students to adopt a lower sense of competence or self-efficacy. Moreover, escalating challenges in the English curriculum may result in diminished self-efficacy in language acquisition. However, the previous literature is not clear as to how students' ECS may follow different growth trajectories, and hence, this study attempted to elucidate the motivational processes in developing self-efficacy and how it is involved in these accompanying trajectories. That is, student perception of self-efficacy is an important construct in understanding motivation given its close correspondence to learning performance and has notably been proven predictive of achievement outcomes. This empirical evidence demonstrates its significant role as a predictor of students' learning, corroborating educators' longitudinal studies that students' self-beliefs regarding academic abilities are crucial to their L2 motivation for improving language proficiency.

In this context, students can identify themselves as highly competent, moderately competent, or incompetent in completing a learning activity or task within an ordinary educational environment (Bandura, 2006). In this line, researchers can investigate how motivation varies across individual students during classroom learning by tracking their ever-changing state of mind. In this study, it has been demonstrated that ECS follows different growth patterns and influences learning outcomes, such as class engagement and achievement. This reveals how language learners need to initiate learning tasks with the self-belief that they will perform them successfully. In particular, language teachers must identify those students in the low but increasing group and encourage them to believe more in their abilities.

In this study, with one exception, ECS beliefs typically followed a decreasing growth pattern. This means that from an applied language learning perspective, it is integral for language teachers to encourage and cultivate specific ECS beliefs that may strongly affect L2 learning outcomes. This can be shown from the decreasing growth trajectories in ECS beliefs identified previously. Thus, based on these findings, this study argues for the importance of L2 Language teachers attempting to identify the distinct growth patterns of ECS, which will enable them to saliently discern the different growth types of L2 self-efficacy beliefs that will follow. Thus, it is crucial for teachers to gain this understanding of promoting particular ECS belief growth patterns, which would be beneficial given this context-rich environment of L2 in secondary schools. All in all, when L2 teachers engage their students in L2 class learning and encourage them to improve their L2 achievement, ECS beliefs, in particular, are one of the most significant factors in supporting academic success.

In sum, the present study is the first to provide empirical evidence for three distinct ECS trajectories and to examine the relationship between these trajectories and target learning outcomes, such as English class comprehension, participation, attitude, and achievement. The difference in ECS effectiveness according to the distinct ECS growth profiles has important policy implications. Educators, policymakers, and parents are likely to find it interesting that the results of this research suggest practical customized prevention and evidenced support for a separate growth profile framework as the recommended approach for L2 students.

Some limitations of this study deserve mention. First, the sample comprised Korean middle school students, limiting the findings' generalization to more diverse populations. Second, the use of self-report to assess for ECS can be questioned. This study also shared its methodological limitations. While growth mixture modeling effectively addresses the heterogeneity of growth trajectories, a limitation of this analysis is the failure to consider the clustering effect at the school level. The current sample showed an average of fewer than five students per school within the group; consequently, the effect of data clustering is expected to be negligible, resulting in unsuccessful model convergence in the multilevel GMM. Future researchers should use multi-level analysis to consider the school level with a larger sample size. Despite these limitations, it is important to note that the present sample is unique for its large number of participants (N = 3,008) and use of longitudinal measurement with the GMM approach. GMM approaches incorporate a mix of exploratory and confirmatory analyses. As a result, employing a principled analytic process for model specification and refinement can assist the researcher in elucidating valuable information about longitudinal change, such as identifying distinct growth forms and to whom these growth characteristics apply.

6. Conclusion

This study may be among the first attempts to employ a longitudinal and person-centered approach to investigate the development of students' L2 ECS. The findings demonstrate significant variations in the initial values and growth rates of middle school students' ECS over time, underscoring the necessity for person-centered methodologies in understanding ECS development. Additionally, students' learning outcomes were correlated with the different trajectories of their ECS. To effectively identify and support different sub-groups of students, particularly those who experience a decline in their ECS or struggle with self-doubt regarding their learning abilities, language teachers should carefully observe the patterns of change in students' self-efficacy and their perceptions of efficacy-enhancing learning experiences. Implementing tailored educational strategies that address the diverse needs of students can be beneficial in fostering ECS. In this regard, differentiated instruction may serve as an effective approach to support students accordingly.

This study discovered that L2 learners' sense of self changed differently over time and that ECS growth factors are important in predicting L2 achievement and class engagement. Because self-efficacy is one of the most influential factors for L2 learning, it appears critical for the L2 teacher to assist students in developing their ECS in accordance with their growth patterns. Language teachers can improve students' ECS through a variety of teaching methods based on their ECS growth patterns.

For example, L2 instructors should give students appropriate differentiated language tasks that they can easily accomplish based on their ECS growth types; hence through these small but accumulated successful experiences, students can build self-beliefs in their perceived competence in L2 learning. In particular, positive feedback and encouragement from teachers can boost students' self-efficacy in the low but increasing group. Those students should be given more opportunities to observe teachers or peers as role models performing tasks successfully than other ECS group students; these vicarious experiences and positive emotions help students develop a positive self-image.

In sum, this study confirmed that self-efficacy is an influential factor in L2 learning. Furthermore, this study takes a developmental view of self-efficacy and considers how the longitudinal perspective can help understand the change of self-efficacy in SLA. This study bridges self-efficacy research in educational psychology to SLA in its investigation of middle school students' English class self-efficacy in the EFL context. More importantly, these findings suggest we need a better understanding of the features of the different ECS growth trajectories and how they may be related to the L2 English learning outcomes. This study will help contribute to a fuller, more comprehensive understanding of L2 class self-efficacy in SLA.

Applicable levels: Secondary

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Appendix

Bivariate Correlations Among All the Indicators over Time

Item	T11	T12	T13	T14	T21	T22	T23	T24	T31	T32	T33	T34	Com	Part	Atti	Ach
T12	.765**	1														
T13	.779**	.688**	1													
T14	.820**	.757**	.818**	1												
T21	.490**	.427**	.470**	.480**	1											
T22	.443**	.473**	.433**	.454**	.739**	1										
T23	.458**	.406**	.492**	.466**	.792**	.694**	1									
T24	.462**	.427**	.461**	.475**	.809**	.745**	.812**	1								
T31	.458**	.408**	.461**	.448**	.532**	.467**	.510**	.512**	1							
T32	.408**	.429**	.402**	.412**	.451**	.496**	.445**	.463**	.757**	1						
T33	.438**	.397**	.468**	.448**	.516**	.462**	.532**	.504**	.817**	.732**	1					
T34	.440**	.400**	.450**	.449**	.501**	.466**	.495**	.507**	.823**	.760**	.845**	1				
Com	.465**	.460**	.482**	.465**	.484**	.470**	.501**	.477**	.629**	.576**	.659**	.632**	1			
Part	.304**	.294**	.314**	.309**	.325**	.341**	.306**	.332**	.467**	.482**	.459**	.472**	.569**	1		
Atti	.371**	.368**	.375**	.384**	.429**	.449**	.419**	.443**	.611**	.626**	.607**	.625**	.610**	.657**	1	
Ach	.322**	.360**	.354**	.332**	.326**	.349**	.339**	.308**	.376**	.396**	.395**	.365**	.504**	.315**	.342**	1

Note. T11 = Item 1 at Time 1; Com = comprehension; Part = participation; Atti = attitude; Ach = achievement score.
$^{**}p < .01$.